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Exploring the relationship between urbanization, energy consumption, and CO_2 emission in MENA countries

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ABSTRACT

This study explored the relationship between urbanization, energy consumption, and CO_2 emission in the MENA countries. The panel model was utilized taking the period 1980–2009 into consideration. Pedroni cointegration test results showed that urbanization, energy consumption and CO_2 emission were cointegrated. The dynamic OLS results also showed that there was a long run bi-directional positive relationship between urbanization, energy consumption, and CO_2 emission. However, the significance of the long run relationship between urbanization, energy consumption, and CO_2 emission varied across the countries based on their level of income and development. Moreover, long and short run bi-directional causal relationships were found between the variables based on the Granger causality test results. From the results of this study it is important for the urban planners and policy makers in the MENA countries to slow the rapid increase in urbanization. The level of energy consumption and CO_2 emission in the MENA countries increased more than double. Thus slowing down the urbanization level can help reduce the level of pollution and energy consumption. In addition, the increased energy efficiency, implementation of energy savings projects, energy conservation, and energy infrastructure outsourcing reduce the level of pollution produced by urban areas.

Contents

1. Introduction

The Middle East and North African (MENA) region has witnessed and is still witnessing high increase in urban growth. In the last three decades, the urban population increased more than 250%. Based on the World Developing Indicators, the urban population in the MENA region increased more than 61% from total population in 2009 and this percentage is expected to rise in the coming years. This rapid increase in urban growth might cause a number of challenges such as the increase in the demand of energy which might be the reason behind MENA's rapid increase in energy consumption and CO_2 emission in the last three decades. In addition, none of the previous studies explored the relationship between energy consumption, CO_2 emission, and urbanization in the MENA countries. This motivated the researcher

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to explore the relationship between urbanization, energy consumption, and CO_2 emission in the MENA region countries, namely Algeria, Bahrain, Djibouti, Egypt, Arab Rep, Iran, Islamic Rep, Iraq, Jordan, Kuwait, Lebanon, Libya, Mauritania, Morocco, Oman, Qatar, Saudi Arabia, Sudan, Syrian Arab Republic, Tunisia, and the United Arab Emirates (UAE). Exploring the relationship between the energy consumption, CO_2 emission and urbanization is important because from this study we can find out whether urbanization is a major source of the energy consumption and CO_2 emission increase in the MENA countries.

A number of studies have explored the relationship between urbanization, energy consumption and CO_2 emission. Li et al. [1], Liu [2,3], Zhang and Lin [4], Wang et al. [5,6] and Parshall et al. [7] found that urbanization was one of the major factors that affected China and the United States energy consumption. Similar results were found in the newly industrialized countries by Hossain [8], in the United States by Clement and Schultz [9], in 208 developed and developing countries by Jorgenson [10] and in Tunisia by Shahbaz and Lean [11]. Donglan et al. [12] also found that the income and energy consumption in urban China had increased the level of CO_2 emission. In addition, Poumanyvong and Kaneko [13] found that urbanization increases CO_2 emission in a number of developed and developing countries. While urbanization affects energy consumption negatively in the low income countries it increases energy consumption in high income countries. The same results were obtained by Poumanyvong et al. [14] who found that urbanization increases transportation energy consumption and the relationship gets stronger the higher the income of the country is. Moreover, Al-mulali et al. [15] found a bi-directional long run relationship between urbanization, energy consumption and CO_2 emission in 84% of the investigated countries and the relationship is affected by the level of development in each country. O'Neill et al. [16] found that China's economic growth effect driven by the increased labor supply and associated with faster urbanization affected both aggregate energy consumption and CO_2 emission. Zhu et al. [17] revealed an inverted U-shape relationship between urbanization and CO_2 emission in 20 emerging countries.

Xiangyang and Guiqiu [18], Liu et al. [19,20], Li et al. [21], and Wang [22] found that urbanization played an important role in increasing CO_2 emission in China. Karaca et al. [23] also found that the urbanization in major cities such as Istanbul increases the pollution level in Turkey. In the Yangtze River Delta which represents the most developed and populated industrial area in China, Gu et al. [24] found that the urbanization process in this area increased the level of pollution. The same results were found in a number of developing countries by Zarzoso and Maruotti [25] and in China by Zhu and Peng [26].

York et al. [27] also found that urbanization had a significant impact in increasing both energy consumption and CO_2 emission in the world. The same results were found in a number of developing countries by Jones [28], in China by Wei et al. [29], in the Asian Pacific region by Zhao and Schroeder [30], in a number of developed and developing countries by Parikh and Shukla [31] and in the Soviet Republics by York [32]. In China, Feng et al. [33] found that urban household energy consumption and CO_2 emission were higher than those of the rural household. However, Chun-sheng et al. [34] found that the CO_2 emission produced by a rural household was much larger than that of the urban household in China. In addition, the population, especially in urban areas, had a strong relationship with CO_2 emission; however, this relationship varied across countries based on the income level. It was negative in high income levels whereas it was positive in other income levels [35]. In addition, urbanization increased the level of energy consumption by transportation in China [36].

2. Data and methodology

The main goal of this study is to examine the relationship between urbanization, energy consumption, and CO_2 emission. To achieve this goal, the panel model will be utilized taking the period 1980–2009 into consideration. This model has been chosen because of the many advantages it has [37]. The models that will be built are specified as follows:

$$EM_{it} = f(URBAN_{it}, ENC_{it}) \tag{1}$$

$$ENC_{it} = f(URBAN_{it}, EM_{it}) \tag{2}$$

where URBAN is the urban population as an indicator of urbanization measured in millions of persons, EM is the total carbon dioxide emission from the consumption of energy measured in million metric tons, and ENC is the total primary energy consumption measured in quadrillion Btu. t denotes time and i denotes the cross section (countries).

The urban population as an indicator was taken from the World Development Indicators (WDI) [38] while the total primary energy consumption and the total carbon dioxide emission from the consumption were taken from the Energy Information Administration (EIA) [39].

2.1. Estimation procedure

The first step is to examine the stationarity of the variables; thus, the panel unit root test will be utilized. Two types of panel unit root tests, namely, Im, Pesaran and Shin, and the ADF Fisher-type tests will be used. If the variables are stationary at the first difference, the Pedroni cointegration test will be used to examine the bi-directional long run relationship between urbanization, energy consumption and CO_2 emission. If the models are cointegrated, the Granger causality based on the vector error-correction model (VECM) will be used to examine both the short and long run bi-directional causal relationships between the variables.

2.2. Panel unit root test

The panel unit root tests have higher power than the unit root tests based on the individual time series which is the reason behind its popularity among researchers. Two types of panel unit root tests, namely, ADF and PP unit root tests, will be used. Both tests are based on the Fisher-type tests. These tests used Fisher's (1932) results to derive tests that combined the p-value from individual unit root tests. These tests were proposed by Maddala and Wu [40] and by Choi [41]. If π_i is defined as the p-value form, any individual unit root test for cross-section will be I. Then, under the null hypothesis of unit root for all N cross-sections, we have the following asymptotic result:

$$-2\sum_{i=1}^{N}\log(\pi_i)\rightarrow x^2_{2N} \tag{3}$$

Choi also shows that

$$Z=\frac{1}{\sqrt{N}_{i=1}}\sum_{i=1}^{N}\Phi^{-1}(\pi_i)\rightarrow N(0,1) \tag{4}$$

where Φ^{-1} is the inverse of the standard normal cumulative distribution function. The null hypothesis for these tests can be written as

$H_0 : \alpha_i = 0$, for all i

On the other hand, the alternative hypothesis can be written as follows:

$$H_1 : \begin{cases} \alpha_i = 0, & for\ i = 1,2,\ldots\ldots N_i \\ \alpha_i < 0 & for\ i = N+1,\ N+2,\ldots,N \end{cases}$$

2.3. Panel cointegration test

The popularity of the panel cointegration grew among researchers due to its high power. The Pedroni cointegration test will be used in this study to examine the bi-directional long run relationship between urbanization, energy consumption and CO_2 emission. Pedroni carried out several tests for panel cointegration that allow for heterogeneous intercepts and trend coefficients across-section. The Pedroni panel cointegration follows the following regression:

$$y_{it} = \alpha_i + \delta_i t + \beta_{1i} x_{1i,t} + \beta_{2i} x_{2i,t} + \ldots + \beta_{Mi} x_{Mi,t} + e_{i,\ t} \tag{5}$$

where t is the number of observations over time, and M is the number of independent variables. It is assumed here that the slope coefficients $\beta_{1i},\ldots,\beta_{Mi}$, and the member specific intercept α_i can vary across each cross-section. Under the null hypothesis of no cointegration, the residual in the equation above e_{it} should be I(1). To find out and test whether the residuals are I(1), it is important to run the following regression for each cross-section:

$$e_{it} = \rho_i e_{it-1} + \mu_{it} \tag{6}$$

or

$$e_{it} = \rho_i e_{it-1} + \sum_{j=1}^{p_i} \psi_{ij} \Delta e_{it-j} + v_{it} \tag{7}$$

Pedroni made two types of alternative hypotheses, namely, the homogeneous alternative (Pedroni terms it the within-dimension test or panel statistics test) and the heterogeneous alternative (between-dimension or group statistics test). The Pedroni panel cointegration statistics are constructed from the residuals. These cointegration statistics are specified as follows:

a. Panel-ρ statistic

$$T\sqrt{N\,Z_{\hat{\rho}N,T-1}} \equiv T\sqrt{N}\left(\sum_{i=1}^{N}\sum_{t=1}^{T}\hat{L}_{11i}^{-2}e_{i,t-1}^{2}\right)^{-1}\sum_{i=1}^{N}\sum_{t=1}^{T}\hat{L}_{11i}^{-2}(\hat{e}_{i,t-1}\Delta\hat{e}_{i,t}-\hat{\vartheta}_i) \tag{8}$$

b. Panel-t statistic

$$Z_{tN,T}^{*} \equiv \left(s_{N,T}^{\sim *2}\sum_{i=1}^{N}\sum_{t=1}^{T}\hat{L}_{11i}^{-2}e_{i,t-1}^{2}\right)^{-1/2}\sum_{i=1}^{N}\sum_{t=1}^{T}\hat{L}_{11i}^{-2}e_{i,t-1}\Delta\hat{e}_{i,t} \tag{9}$$

c. Group-ρ statistic

$$TN^{-1/2}\tilde{Z}_{\hat{\rho}N,\ T-1} \equiv TN^{-1/2}\sum_{i=1}^{N}\left(\sum_{t=1}^{T}\hat{e}_{i,t-1}^{2}\right)^{-1}\sum_{t=1}^{T}(e_{i,t-1}\Delta\hat{e}_{i,t}-\hat{\vartheta}_i) \tag{10}$$

d. Group-t statistic

$$N^{-1/2}\tilde{Z}_{tN,T}^{*} \equiv N^{-1/2}\sum_{i=1}^{N}\left(\sum_{t=1}^{T}\hat{s}_i^{*2}\hat{e}_{i,t-1}^{2}\right)^{-1/2}\sum_{t=1}^{T}\hat{e}_{i,t-1}\Delta\hat{e}_{i,t} \tag{11}$$

where

$$\hat{\vartheta}_i = \frac{1}{2}(\hat{\sigma}_i^2 - \hat{s}_i^2)$$

and

$$s_{N,T}^{*2} \equiv \frac{1}{N}\sum_{i}^{N} s_i^{*2}$$

The optimal mean and variance term can be applied when the panel cointegration test statistics are calculated. This helps the test statistics to be asymptotically standard normally distributed.

If the models are cointegrated, the panel dynamic OLS (DOLS) will be utilized to examine whether there is a negative or a positive long run relationship between the variables. The panel DOLS was proposed by Pedroni [42]. The DOLS method involves expanding the cointegration regression with lags and leads resulting in a cointegration equation error term which is orthogonal to the entire history of the stochastic regressor innovations:

$$y_{it} = X_{it}'\beta + D_{1it}'\gamma_1 + \sum_{j=-q}^{r}\Delta X_{it+j}\delta + v_{1it} \tag{12}$$

Adding q lags and r leads of the different regressors eliminates all the long run correlations between the residuals.

2.4. Panel Granger causality

The Granger causality test will be utilized in this study to examine the causal relationship between urbanization, energy consumption, and CO_2 emission. If the models are cointegrated, the Granger causality based on the vector error-correction model (VECM) will be used. The VECM Granger causality can show both the short run causal relationship based on the F-statistics and the long run causal relationship based on the error correction term ect (-1). The VECM models can be presented as follows:

$$\Delta URBAN_{it} = \alpha_{it} + \beta_{it}ect_{it-1} + \sum_{i=1}^{l}\xi_{it}\Delta URBAN_{it-1} + \sum_{i=1}^{l}\varphi_{it}\Delta(ENC)_{it-1} + \sum_{i=1}^{l}\delta_{it}\Delta(EM) + \mu_{it} \tag{13}$$

$$\Delta ENC_{it} = \alpha_{it} + \beta_{it}ect_{it-1} + \sum_{i=1}^{l}\xi_{it}\Delta ENC_{it-1} + \sum_{i=1}^{l}\varphi_{it}\Delta(URBAN)_{it-1} + \sum_{i=1}^{l}\delta_{it}\Delta(EM) + \mu_{it} \tag{14}$$

$$\Delta EM_{it} = \alpha_{it} + \beta_{it}ect_{it-1} + \sum_{i=1}^{l}\xi_{it}\Delta EM_{it-1} + \sum_{i=1}^{l}\varphi_{it}\Delta(URBAN)_{it-1} + \sum_{i=1}^{l}\delta_{it}\Delta(ENC) + \mu_{it} \tag{15}$$

Δ is the first difference operator, α_{it} is the constant term, β_{it}, ξ_{it}, φ_{it}, and δ_{it}, are the parameters, ect_{it-1} is the lagged error correction term obtained from the cointegrating equation and μ_{it} is the white noise error.

On the other hand, if the models are not cointegrated, the Granger causality based on the Vector autoregressive (VAR) model which captures only the short run causal relationship will be used. Granger causality based on the VAR model can be presented as follows:

$$\Delta URBAN_{it} = \alpha_{it} + \sum_{i=1}^{l}\xi_{it}\Delta URBAN_{it-1} + \sum_{i=1}^{l}\varphi_{it}\Delta(ENC)_{it-1} + \sum_{i=1}^{l}\delta_{it}\Delta(EM) + \mu_{it} \tag{16}$$

$$\Delta ENC_{it} = \alpha_{it} + \sum_{i=1}^{l} \xi_{it} \Delta ENC_{it-1} + \sum_{i=1}^{l} \varphi_{it} \Delta(URBAN)_{it-1} + \sum_{i=1}^{l} \delta_{it} \Delta(EM) + \mu_{it} \quad (17)$$

$$\Delta EM_{it} = \alpha_{it} + \sum_{i=1}^{l} \xi_{it} \Delta EM_{it-1} + \sum_{i=1}^{l} \varphi_{it} \Delta(URBAN)_{it-1} + \sum_{i=1}^{i} \delta_{it} \Delta(ENC) + \mu_{it} \quad (18)$$

3. Empirical results

The Pedroni cointegration test requires the variables to be stationary at the first difference; thus the panel unit root test is used. Table 1 reviews the ADF-Fisher Chi-square and the PP-Fisher Chi-square test results which clearly show that all the variables are not stationary at levels. However, all the variables are stationary at the first difference rejecting the null hypothesis at 1% level of significance. This indicates that the variables contain a panel unit root.

Since the variables are stationary at the first difference, the Pedroni cointegration test will be utilized. Table 2 reviews the Pedroni cointegration test results. The results gained from the ENC model show that ten statistics were significant rejecting the null hypothesis of no cointegration indicating that both urbanization and CO_2 emission have a long run relationship with energy consumption. Lastly, the results gained from the EM model show that eight statistics were significant rejecting the null hypothesis of no cointegration. This indicates that energy consumption and urbanization have a long run relationship with CO_2 emission. Thus, the Pedroni cointegration test results reveal that there is a bi-directional long run relationship between energy consumption, CO_2 emission and urbanization.

Since the variables are cointegrated, the dynamic OLS (DOLS) will be utilized. Table 3 shows the dynamic OLS test results. From the results it can be seen that the significance of the relationship between urbanization, energy consumption, and CO_2 emission varied across the countries based on their levels of income and development. The long run positive relationship between urbanization, energy consumption and CO_2 emission is more significant in high and upper middle income countries compared to the lower middle income countries. On the other hand, the relationship between the variables is negative in low income countries such as Mauritania. Thus the relationship between the variables is determined by the income and development levels. However, this study will focus on the panel effect since we are using the panel analysis. The panel DOLS test results show that both energy consumption and CO_2 emission have a positive long run relationship with urbanization. 1% increase in energy consumption and CO_2 emission will increase urbanization by 0.865833% and 0.681991% respectively. In addition, the 1% increase in urbanization and CO_2 emission will increase energy consumption by 0.571683% and 0.883922% respectively. Finally, the results show that 1% increase in urbanization will increase CO_2 emission by 0.521975%. Moreover, 1% increase in energy consumption will increase CO_2 emission by 0.826646[a] %. The DOLS results show that there is a positive bi-directional long run relationship between energy consumption, CO_2 emission, and urbanization. From the results above it is clear that the increase in urbanization will increase both energy consumption and CO_2 emission in the long run.

Since the variables are cointegrated, the Granger causality based on the VECM will be utilized. Table 4 review the Granger causality test results which reveal that there is a bi-directional causal relationship between urbanization, energy consumption, and CO_2 emission based on the error correction term ect (−1). The short causal relationship shows a bi-directional positive causal relationship between CO_2 emission and urbanization and between energy consumption and CO_2 emission. There is also a one way positive causal relationship from urbanization to energy consumption.

Table 1
Panel unit root test results.

Variable	ADF-Fisher Chi-square			
	Level		First difference	
	Intercept	Intercept and trend	Intercept	Intercept and trend
URBAN	16.0588	28.8762	161.000 [a]	142.618 [a]
ENC	7.24731	22.1065	111.695 [a]	96.2227 [a]
EM	23.2044	19.8512	156.299 [a]	114.394 [a]
	PP-Fisher Chi-square			
URBAN	29.6784	19.3447	177.143 [a]	152.318 [a]
ENC	7.90987	32.8718	394.819 [a]	1016.78 [a]
EM	38.1417	34.0239	389.877 [a]	906.160 [a]

Note: the unit root tests were carried out with individual trends and intercepts for each variable, and the optimal lag lengths were selected automatically using the Schwarz information criteria.
Indicates significance at 1% and 5% levels.

[a] Indicates significance at 1% and 5% levels.

Table 2
Pedroni cointegration test results.

	ENC model	EM model
Alternative hypothesis: common AR coefs. (within-dimension)		
Panel v-statistic	2.844874 [a]	1.069360
Panel rho-statistic	−1.695052 [b]	−1.940536 [b]
Panel PP-statistic	−2.785714 [a]	−5.422531 [a]
Panel ADF-statistic	−3.327934 [a]	−5.422623 [a]
Panel v-statistic (Weighted statistic)	1.143215	−1.732028
Panel rho-statistic (Weighted statistic)	−3.236188 [a]	−0.024241
Panel PP-statistic (Weighted statistic)	−4.647079 [a]	−2.646601 [a]
Panel ADF-statistic (Weighted statistic)	−4.702239 [a]	−2.755977 [a]
Alternative hypothesis: individual AR coefs. (between-dimension)		
Group rho-statistic	−3.485617 [a]	−3.610724 [a]
Group PP-statistic	−4.666581 [a]	−5.966276 [a]
Group ADF-statistic	−4.505089 [a]	−5.686275 [a]

Denotes significance at 1%, 5% and 10%; we use the automatic selection based on Schwarz to choose the optimal lag length.

[a] Denotes significance at 1%, 5% and 10%; we use the automatic selection based on Schwarz to choose the optimal lag length.

[b] Denotes significance at 1%, 5% and 10%; we use the automatic selection based on Schwarz to choose the optimal lag length.

4. Conclusion and discussion

The rapid increase in the levels of urbanization, energy consumption, and CO_2 emission in the MENA countries has motivated the researcher to explore the relationship between these variables. To achieve this goal, the panel model was utilized taking the period 1980–2009 into consideration. The Pedroni cointegration test results showed that urbanization, energy consumption, and CO_2 emission were cointegrated. The dynamic OLS results showed that there was a positive bi-directional long run relationship between urbanization, energy consumption, and CO_2

Table 3
The dynamic OLS test results.

	URBAN as the depended variable		ENC as the dependent variable		EM as the dependent variable	
	ENC	EM	URBAN	EM	URBAN	ENC
Algeria	0.393530 [a]	0.699759 [a]	1.468231 [a]	0.852804 [a]	0.560314 [a]	0.608594 [a]
Bahrain	2.048767 [a]	0.152598 [a]	0.193759 [a]	0.159218 [a]	0.410222 [a]	2.164659 [a]
Djibouti	2.901084 [b]	2.566031 [b]	2.394559 [c]	0.415538 [c]	0.085340 [c]	1.990326 [c]
Egypt	0.110794 [c]	0.239291 [c]	1.844968 [c]	1.232062 [c]	0.736370 [b]	0.877338 [c]
Iran	0.347081 [b]	0.156794 [a]	0.675201 [a]	2.302840 [a]	0.032180 [b]	0.635828 [a]
Iraq	0.310549 [c]	0.147413 [c]	0.434815 [c]	0.819709 [c]	1.293646 [c]	0.780348 [c]
Jordan	2.325041 [a]	1.205672 [b]	0.349752 [a]	0.998112 [a]	0.350243 [a]	0.842465 [a]
Kuwait	0.377194 [a]	0.386795 [a]	0.255995 [b]	0.842753 [a]	0.678633 [b]	0.346596 [a]
Lebanon	0.869312 [a]	1.206276 [a]	0.429232 [b]	1.081201 [a]	0.498295 [a]	0.874244 [a]
Libya	0.814200 [a]	0.479934 [b]	0.593018 [a]	0.524912 [a]	0.135407 [a]	0.837199 [a]
Mauritania	−0.753241 [c]	−0.321710 [c]	−0.560105 [b]	−0.976451 [a]	−0.215952 [b]	−0.999587 [a]
Morocco	0.893660 [a]	0.347603 [a]	0.215918 [b]	1.218430 [a]	0.611401 [a]	0.417404 [a]
Oman	0.105560 [a]	0.729784 [a]	0.326549 [a]	0.821088 [a]	0.097488 [b]	1.060345 [a]
Qatar	1.258889 [b]	0.408488 [b]	0.319526 [a]	1.241453 [a]	0.602156 [a]	0.984386 [a]
Saudi Arabia	0.938222 [a]	0.210636 [b]	0.704092 [a]	0.558777 [a]	0.591067 [b]	0.305996 [b]
Sudan	0.452048 [c]	0.270250 [c]	0.743752 [c]	1.346206 [b]	1.350971 [c]	1.244353 [c]
Syria	1.423417 [b]	0.619065 [c]	0.119240 [c]	0.841189 [c]	1.207618 [c]	1.008984 [c]
Tunisia	0.798178 [a]	1.065079 [a]	0.592585 [a]	1.121626 [a]	0.563196 [a]	0.801184 [a]
UAE	1.291256 [a]	1.866526 [a]	0.282187 [a]	1.402191 [a]	0.222164 [a]	0.699346 [a]
Yemen	0.411108	1.203529 [c]	0.050392 [c]	0.874777 [a]	0.628742 [c]	1.052904 [c]
Panel	0.865833 [b]	0.681991 [b]	0.571683 [b]	0.883922 [a]	0.521975 [b]	0.826646 [a]

Note: the numbers presented in the table are the slope coefficients.

[a] Denotes significance at 1%, 5%, and 10% levels.
[b] Denotes significance at 1%, 5%, and 10% levels.
[c] Denotes significance at 1%, 5%, and 10% levels.

Table 4
Panel Granger causality test results.

	The independent variables			
	Short run causal relationship		Long run causal relationship	
	ΔURBAN	ΔENC	ΔEM	ect (−1)
The dependent variable				
ΔURBAN	–	0.252132	1.733813 [c]	−1.733813 [c]
ΔENC	5.945357 [a]	–	1.871525 [c]	−3.317732 [a]
ΔEM	2.768967 [a]	5.284918 [a]	–	−1.442078 [a]

Notes: the null hypothesis is that there is no causal relationship between variables, and Δ is the difference operator. ect (−1) represents the error correction term lagged one period.
Indicates 1%, 5%, and 10% significant levels.

[a] Indicates 1%, 5%, and 10% significant levels.
[c] Indicates 1%, 5%, and 10% significant levels.

emission. In addition, the significance of the relationship between urbanization, energy consumption, and CO_2 emission increases the higher the country's level of income and development is. Moreover, the Granger causality results reveal that there were long and short run causal relationships between the variables. The results clearly showed that urbanization had played an important role in increasing energy consumption and CO_2 emission in the MENA region since most of the energy consumption comes from fossil fuels which are responsible for more than 99% of total energy consumption.

From the results of this study it is important for the urban planners and policy makers in the MENA countries to slow the rapid increase in urbanization. The level of energy consumption and CO_2 emission in the MENA countries increased more than double. Thus slowing down the urbanization level can help reduce the level of pollution. In addition, the increased energy efficiency, implementation of energy savings projects, energy conservation, and energy infrastructure outsourcing reduce the level of pollution produced by urban areas.

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